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On the Stability of the German Beveridge Curve

- A Spatial Econometric Perspective

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Abstract. In this paper, the framework of the aggregated Beveridge curve is used to investigate the effectiveness of the job matching process using German regional labour market data. For a fixed matching technology, the Beveridge curve postulates a negative relationship between the unemployment rate and the rate of vacancies, which is efficiently estimated using spatial econometric techniques. The eigenfunction decomposition approach suggested by Griffith (2000, 2003) is the workhorse to identify spatial and non-spatial components. As the significance of the spatial pattern might vary over time, inference is conducted on the base of a spatial SUR model. Shifts of the Beveridge curve will affect its position, and time series estimates on this parameter are obtained. In contrast to findings for the US and the UK, the results provide serious indication that the degree of job mismatch has increased over the last decade. Although the outward shift of the Beveridge curve can be explained by structural factors such as the evolution of long term unemployment, it is also affected by business cycle fluctuations. The role of cyclical factors threatens the stability property of the curve. The relationship might be inappropriate to investigate policy measures directed to improve the mismatch, such as labour market reforms.

Keywords: Beveridge curve, job mismatch, business cycle, long-term unemployment, spatial SUR model

JEL: C21, C23, E24, E32

1. Introduction

In this paper, we use the aggregated Beveridge curve to examine the effectiveness of the matching process in the German macroeconomic labour market. The efficiency at which workers are matched to available jobs is of key relevance for the duration of unemployment spells and the ability of the economy to utilize its resources. Due to coordination failures the matching process is imperfect. Even in the case of vacancies, a mismatch between the skills the workers supply and the skills employers demand can prevent the completion of a working contract. Eventually, the mismatch may have become more pronounced in recent years, since the pace of structural change in the labour market has accelerated. The workplace transforms increasingly to a high-tech and service oriented area, where higher employee managing capabilities are also involved (Bresnahan, Brynjolfsson and Hitt, 2002).

For a fixed matching technology, the Beveridge curve postulates a negative relationship between the unemployment rate (u) and the rate of vacancies (v), both in terms of the labour force. It is important to note that this relationship is not derived from optimization behaviour of individuals and therefore, it should not be interpreted in a structural sense. Instead, the curve shows an empirical correlation arising indirectly from the decisions of workers and employers regarding hiring and firing, accumulation of human capital etc (Blanchard and Diamond, 1989). In periods of rising economic activity, vacancies increase. Hence it is easier for the unemployed to find a job, and unemployment will decline. Likewise, in periods of weak activity, vacancies are closed, and workers enter the unemployed. While movements along a Beveridge curve reflect adjustments over the business cycle, shifts are usually seen as evidence for structural change. In general, the position of the Beveridge curve in the (u,v) space is related to the degree of frictions in the labour market. The closer the curve to the origin, the smaller are the frictions, and the more efficient is the matching technology.

An outward shift of the curve can be interpreted as an indicator for an increased mismatch, because of deterioration in human capital of the unemployed, or a higher availability of unemployment benefits, which reduces the willingness of the unemployed to fill out the vacancies. Furthermore, changes in the conditions for special groups of the labour force could be relevant. For example, the employment and income perspectives have worsened for the unskilled in the process of economic integration, as their jobs have been exported to the low-wage countries (Nickell and Bell, 1995). If the Beveridge curve for the low skilled has drifted outwards, a corresponding shift could also occur in the aggregated curve (Song and Webster, 2003). Changing trends in the demographic composition of the labour force because of an increase in the participation rate of women or immigration might also be important.

In order to get efficient estimates of the relationship, the empirical analysis refers to a sample of 180 regional labour markets. The regions are separated on the base of flows of the job commuters and correspond to travel-to-work areas. Due to shocks common to all or several regions, regional labour markets are not unrelated. They are tied together due to their location, and spillovers might lead to spatial effects. Since these patterns can affect the relationship between unemployment and vacancies, ordinary regressions are eventually biased. Therefore, the Beveridge curve is efficiently estimated using a spatial econonometric procedure, where the eigenfunction decomposition method suggested by Griffith (2000, 2003) is employed to identify spatial and non-spatial components. As the spatial pattern may vary over time, inference is conducted using a spatial SUR framework. To the best of our knowledge, no previous study has appropriately controlled for dependencies across the panel members so far. In addition, the empirical strategy reveals time series evidence concerning the position of the curve. Therefore, indication regarding the driving forces of shifts in the Beveridge curve can be provided.

The analysis draws a number of interesting results. In contrast to the panel framework used by Börsch-Supan (1991) for 9 West German regions, a negative relationship in the (u,v) space clearly emerges from the spatial estimation exercise. Even more important, we present strong evidence for an ongoing outward shift of the Beveridge curve for the German economy. This is in contrast to findings for other countries including the US, the UK, and Canada, where labour market trends have been more favourable over the past decade (see Bleakley and Fuhrer, 1997, Katz and Krueger, 1999, Archambault and Fortin, 2001, Valletta, 2005). On the one hand, the outward shift of the German Beveridge curve can be traced to unfavourable structural factors. In particular, the development of the long term unemployment rate turns out to be significant, which points to the presence of hysteresis in the evolution of unemployment. On the other hand, business cycle fluctuations are relevant in explaining the shifts of the curve. The results on the role of cyclical factors are in line with some recent US and UK studies which have challenged the stability property of the Beveridge curve, including Wall and Zoega (2002) and Valletta (2005). As a consequence, the relationship might not be a valid tool to investigate the success of economic policies directed to improve the mismatch, such as appropriate labour market reforms.

The paper is organised as follows. In section 2, the Beveridge curve is derived from the mismatch function. Then, spatial econometric techniques are discussed (section 3). The empirical analysis proceeds in three steps. After describing the data set, the concept of regional labour markets is presented (section 4). The estimation of the curve is carried out in section 5, while section 6 presents evidence regarding the determinants of shifts in the relationship. Finally, section 7 concludes.

2 Derivation of the Beveridge curve

The Blanchard and Diamond (1989) model is the starting point for the derivation of the Beveridge curve. A rise in unemployment can result either from unfavourable structural conditions or business cycle slowdowns. If the source is a lack in aggregate demand, a corresponding decrease of the vacancy rate can be observed. The number of new hires (M) in each period t is explained by a matching function

(1) $$M = M(U,V), \quad \partial M / \partial U > 0, \; \partial M / \partial V > 0$$

and depends on the levels of persons unemployed (U) and the number of vacant posts of firms (V). The matching function reveals the effectiveness of the technology that brings workers searching for jobs together with employers searching for workers. If the number of workers searching for jobs or the number of employers searching for workers increase, the number of matches will also increase. For example, workers will be less choosy to accept job offers in periods of higher unemployment. The matching process can be specified in terms of a Cobb-Douglas production function with constant returns to scale

(2) $$M = AU^{\gamma}V^{1-\gamma}$$

where $0<\gamma<1$ (see Petrongolo and Pissarides, 2001). Doubling both unemployment and vacancies will double the number of hires. The matching technology parameter $A>0$ controls for possible shifts in the Beveridge curve. In equilibrium, the number of matches M will be equal to the number of separations S. Dividing M and S by the labour force L, we obtain the implicit form of the Beveridge curve,

(3) $$s = au^{\gamma}v^{1-\gamma},$$

with $a = A/L$, $u = U/L$ and $v = V/L$. For a given the separation rate $s = S/L$, a convex relationship between the unemployment rate and the rate of vacancies is apparent. Taking the logs of both sides of (3), the log-log form of the Beveridge curve

(4) $$log\, u = (log\, a - log\, s)/\gamma + [(1-\gamma)/\gamma]\cdot log\, v$$

is supported.

While shocks in aggregate demand are expected to trigger counterclockwise cyclical adjustment along the curve leaving its position unaffected, shifts of the curve arise from structural factors (Petrongolo and Pissarides, 2001). Therefore, the Beveridge relationship is unlikely to be stable over sufficiently long periods of time. Structural shocks show up in shifts of the technology parameter, and might reflect the ability of the unemployed to match the vacancies. The matching technology might change due to changes in the effectiveness of the searching process or the implementation of labour market reforms, see Nickell, Nunziata, Ochel and Quintini (2001) and Pissarides (2003). Furthermore, hysteresis in the course of unemployment could affect the position of the curve. In fact, a movement along the curve would imply an outward shift in the next period. Hysteresis might be traced to human capital deterioration of the long term unemployed or a negative perception of long unemployment spells on employers, see Pissarides (1992) and Blanchard and Diamond (1994).

Given that shifts can be solely attributed to structural factors, the framework could provide important insights to policymakers. For example, if reforms try to improve the efficiency of the search process on the labour market, their success could be measured by a pronounced inward shift of the Beveridge curve. If, however, other factors like business cycle fluctuations are also relevant in explaining the shifts, this evidence would be seriously biased.

3 Spatial filtering and spatial SUR models

As the Beveridge curve is estimated with regional data, dependencies between regions have to be taken into account. They can arise from common or idiosyncratic shocks, thereby generating spillovers between the spatial units. As a result, geo-referenced variables will be spatially autocorrelated. In any case significance tests of the regression coefficients are invalid. In addition, depending on the particular spatial pattern, estimated regression coefficients can be seriously biased (Anselin 1988). In order to separate the spatial and non-spatial components of the series that enter the regression model, appropriate filter methods have been developed. In this paper, the eigenfunction decomposition approach suggested by Griffith (2000, 2003) is applied. Filtering relies on a decomposition of Moran's *I*,

$$(5) \qquad MI = \boldsymbol{x}'\boldsymbol{W}\boldsymbol{x} \,/\, \boldsymbol{x}'\boldsymbol{x}$$

which is an overall measure for the spatial autocorrelation present in a variable $\boldsymbol{x}$. In particular, $\boldsymbol{x}$ holds the observations for N regions, measured in deviations from their mean. $\boldsymbol{W}$ is a binary contiguity matrix that stores information on the neighbourhoods of the spatial units. The element w_{ij} is equal to 1, if region j shares a common border with region i and 0 otherwise (see Anselin, 1988). Moran's I can be expressed as a weighted sum of the eigenvalues of the matrix

$$(6) \qquad \boldsymbol{C} = (\boldsymbol{I}_N - \mathbf{1}\mathrm{x}\mathbf{1}'/N)\boldsymbol{W}(\boldsymbol{I}_N - \mathbf{1}\mathrm{x}\mathbf{1}'/N)$$

where $\boldsymbol{I}_N$ is the N-dimensional identity matrix and $\mathbf{1}$ a vector of ones (Tiefelsdorf and Boots 1995, Griffith 1996). The separation of the spatial from the nonspatial components is done by the orthogonal eigenvectors of the $\boldsymbol{C}$ matrix. Specifically, spatial dependencies are represented by a set of relevant eigenvectors, S, used in the cross section regression

(7) $$\boldsymbol{y} = \beta_0 + \beta_1 \boldsymbol{x}^* + \sum_S \gamma_j \boldsymbol{\omega}_j + \boldsymbol{u}\,,$$

where $\boldsymbol{u}$ is the vector of errors and the set S includes significant eigenvectors $\boldsymbol{\omega}_j$ of the $\boldsymbol{C}$ matrix.

The nonspatial part $\boldsymbol{x}^*$ of the explanatory variable is given by the OLS residuals from a regression of $\boldsymbol{x}$ on the relevant eigenvectors (Griffith 2000, 2003). As the eigenvectors identify orthogonal geographic patterns, their impact can be tested by stepwise regression. To be considered as candidates, they must represent substantial spatial autocorrelation. If one relates the MI values of the spatial components to their maximum value ($MI_{\max}$) a qualitative assessment of spatial autocorrelation can be obtained. Specifically, the eigenvectors could be of potential relevance, if the ratio MI/MI_{max} exceeds a lower bound of 0.25. (Griffith 2003). As the linear combination of eigenvectors accounts for spatial dependencies, the errors of the regression are whitened.

With panel data, the decomposition is required for each period t, as the spatial patterns can vary over time. Generally, dependencies will exist across space and time. Therefore, instead of estimating a set of unrelated cross-section equations, a spatial SUR analysis is preferable (Anselin, 1988). In particular, the system

(8) $$y_{ti} = \beta_{t0} + \beta_{t1} x^*_{ti} + \sum_{S_t} \gamma_{tj} \omega_{ji} + u_{ti}$$

of which the time-wise covariance structure is given by

(9) $$\boldsymbol{\Sigma}^* = \boldsymbol{\Sigma} \otimes \boldsymbol{I}_{N\cdot},$$

is formed by the periods of time for all N spatial units (i=1,.., N). The TxT covariance matrix $\boldsymbol{\Sigma}$ is composed of the error variances and covariances σ_{ts} (t,s=1,…, T). Provided that $T < N$, $\boldsymbol{\Sigma}$ can be estimated directly from the data.

Since the β parameters are allowed to vary over time (t=1,..,T), annual Beveridge curves will be obtained. The sets S_t of eigenvectors may include different elements. In the first step, all candidate eigenvectors are included successively for each period and tested for significance. Eigenvectors with significance equal or lower than 0.05 are kept in the model, while eigenvectors with p-values above 0.05 are removed. If the residuals of the t-th year pass the Moran test for spatial autocorrelation, the set S_t will be determined.

Otherwise, in a second step, eigenvectors which are significant at the 0.10 level are additionally considered.

4 Regional labour markets and data

To investigate the Beveridge curve for the unified Germany, panel data on the stock of unemployed and vacancies are used over the 1992-2004 period. Both series are reported by the Federal Agency for Employment for overall 870 local agencies. The numbers of unemployed cover registered unemployed who are searching for a job. On the one hand, people who are searching for a short-time work and those not eligible to unemployment benefits are not recorded. Thus, hidden unemployment is excluded from the official figures. On the other hand, some of the unemployed could just register to receive unemployment benefits without really searching for a job.

Data on vacancies have to be also interpreted with care. As the vacancies notified cover only a fraction of the actual stock, detailed knowledge of the reported shares (*Meldequoten*) would be desirable for adjusting the raw data. But, time varying shares from a survey of the Federal Agency of Employment are only reported for West and East Germany as a whole. While the shares in West Germany range from 30 to 39% during the period 1992-2004, they vary between 24 and 42% in the Eastern part of the country (IAB, 2005). We have applied these reported share series for an East-West adjustment of vacancies. Using series on people employed in 439 German districts (CD *Statistik regiona*l, Federal Statistical Office Germany), regional disaggregated labour force series are obtained.

Both labour agencies (*Dienststellenbezirke*) and districts (*Kreise*) do not meet the requirements of functional regions. On average, 53% of the employees bounded to the social security system in local authority areas are commuters who travel to their workplaces across administrative boundaries. Since the labour agencies are in most instances parts of the districts, the percentage of commuters across these spatial units will be even larger. Thus, the modifiable areal unit problem is expected to affect the spatial study of the Beveridge curve by generating artificial spatial patterns (Heywood, 1998).

Spatial autocorrelation due to inadequate delineation of areal units is largely avoided by working with travel-to-work areas. In our spatial analysis we therefore refer to labour market regions that are delineated by commuter flows. Using data on job commuters across German districts, Eckey (2001) defined 180 regional labour markets of which 133 are located in the Western and 47 in the Eastern part of Germany. With these functional regions the average share of commuters decreases from 53 to 21%. On average a regional labour market consists of 2.4 districts and 4.8 agencies.

For explaining possible shifts of the German Beveridge curve we draw attention both on structural and cyclical variables. For the most part, time series of structural factors like the long term unemployment rate are only available on a highly aggregated level. The long term unemployment rate has been taken from the OECD (2005) database and refers to the share of the long term (longer than 1 year) unemployed in overall unemployment. Likewise, the OECD (2005) has provided time series data on various labour market institutions, such as union densities, active labour market policies and measures related to the tax and transfer system. While structural and institutional variables are intended to capture the effects of supply shocks on shifts in the (u,v) space, the use of a cyclical variable allows for testing the role of demand shocks for both adjustment processes along a curve and shifts of the relation. Cyclical fluctuations are measured by the output gap between potential and actual GDP. In order to allow for a nonlinear GDP trend, we employ the Hodrick-Prescott filtered series as a proxy for potential GDP (Hodrick and Prescott, 1981). GDP data are taken from the *Statistisches Jahrbuch* of the German Federal Statistical Office.

5 Econometric analysis of the German Beveridge curve

Spatial panel analysis enables us to estimate annual German Beveridge curves. Our approach proves to be favourable for testing the stability of the curve. By means of this strategy, the restrictive approach using time-dependent functions for assessing changes in matching efficiency is avoided. For the most part, variables playing a role as possible causes of shifts of the unemployment-vacancy relationship are only available at a highly aggregated regional level. As time-dependent intercepts and slopes of the Beveridge curves are available from spatial SUR estimation, the impact of structural and cyclical factors on the location of the German Beveridge curve in (u,v) space can be investigated in a time series analysis.

-Table 1 about here-

Due to huge differences in unemployment between the Eastern and Western part of the country, a dummy variable for East Germany is introduced. Furthermore, spatial components are included in order to capture regional dependencies in the unemployment rates. Table 1 shows the results of the spatial SUR models. In addition, non-spatial (GLS) variants are reported for the sake of comparison. All intercepts are very precisely estimated with both procedures. The Wald coefficient tests clearly reject the null of equal intercepts. Figure 1 exhibits a similar cyclical pattern of the GLS and spatial SUR intercepts which does not seem to be stationary but slightly upward trended. On average, matching efficiency deteriorates by 0.7 per cent per annum. The nonspatial GLS variant underestimates this rate by 0.2 percentage points. Estimates of the slope parameter show in all but one case the expected negative sign. A unique Beveride curve is distinctly rejected by the Wald tests.

-Figure 1 about here-

Both empirical approaches uniformly disclose an effective (u,v) relation only for the subperiod 1992-1995. Unlike GLS spatial SUR does not detect a significant relation between unemployment and vacancy rates in the period 1996-2000. In the last part of the sample (2001-2004) the Beveridge curve is partiallly suspended by GLS as opposed to spatial SUR. Both approaches reveal a high steepness of the (u,v) relationship. This is in line with the findings of panel studies on the Portuguese and British Beveridge curves (Modest, 1996, Wall and Zoega, 2002), but in contrast to former time series analyses of job mismatch. Especially, an increase in the vacancy rate by 10 percent is accompanied by a decrease in the unemployment rate by about 1.2 per cent in equilibrium. Because of the higher efficiency of panel estimation, mismatch indicators based on the time series estimates should be dealt with caution.

Although the goodness of fit appears to be somewhat better with GLS than with spatial SUR, highly spatially autocorrelated residuals point to misspecification of the nonspatial Beveridge relations. In particular, spatial residual autocorrelation invalidates statistical inference in the nonspatial GLS model (see Anselin, 1988). As the panel Durbin-Watson statistic of 1.484 falls well below the extrapolated lower five per cent significance point of 1.841, GLS residuals show additionally positive serial correlation of the errors over time (Bhargava, Franzini and Narendranathan, 1982). Spatial dependencies can be adequately captured by spatial components formed as linear combinations of eigenvectors of the $\boldsymbol{C}$ matrix. In none of the spatial SUR specifications, Moran's I of the residuals turns out to be significant at any customary level. Because of the large number of spatial components, the range of indeterminateness of the panel Durbin-Watson statistic is considerably extended. Although the Panel DW of 1.846 clearly exceeds the lower critical value at a 5% significance level, the testing decision remains inconclusive. Because a certain subset of eigenvectors $\{\boldsymbol{\omega}_j$, j=1, 2, 7, 10, 15, 20, 21, 33, 39, 47$\}$ turns out to be relevant in almost every year, the spatial pattern of dependency is stabilised to a certain degree over time.

In 1992 and in the period 2000-2002, MI/MI_{max} ratios fall in the interval [0.75; 0.90) which implies strong spatial autocorrelation (MI_{max}=1.145). This is reflected by a conspicuous Moran scatterplot trend. All other points are identified as periods of moderate spatial autocorrelation with a noticeable scatterplot trend ($0.50 \leq MI/MI_{max} < 0.75$). However, as the MI/MI_{max} ratios range between 0.679 and 0.785, they are closely concentrated around the MI bound of 0.75. In this case the map patterns must not necessarily differ perceptibly for MI values belonging to adjacent classes.

-Figure 2 about here-

Apart from 1992, comparable map patterns of the spatial components occur in two subperiods (figure 2). In all years considered, clusters of the two lowest value classes are located in the southern part of Germany. While in the periods 1993/2003-2004 a clustering of high component values is found in the north-Eastern and Northwestern part of the country, they mainly shift to the Northwestern part in the second half of the 1990s. In 1992 high-value clusters were stronger concentrated in East Germany. Overall, the spatial patterns turn out to be very stable in the south over the entire sample period, whereas some larger changes between the subperiods can be particularly detected in the Eastern part of Germany.

6 Impacts of institutional and cyclical factors on matching efficiency

Spatial SUR models have revealed the instability of the German Beveridge curve over the 1992-2004 period. The estimates of the intercept and the slope parameter are not unique but vary within the sample. As both parameters are expected to be affected by adjustment processes along a given (u,v) relationship as well as by shifts of this curve, it is difficult to establish the role of business cycle fluctuations for the stability of the curve. Theoretically, Bowden (1980) has shown that in case of a constant matching probability, changes in aggregate demand or real wages initiate a counterclockwise adjustment process around the Beveridge curve if vacancies will be more flexible than the unemployed. If the matching probability is a function of the reservation wage and productivity, the (u,v) curve becomes unstable over the business cycle (Pissarides, 1985; Börsch-Supan, 1991).

Time series estimates of the intercept and slope parameters of annual Beveridge curves can shed some light on the role of the business cycle for the stability of the (u,v) relation. Although adjustment processes in form of counterclockwise loops can temporarily move the intercept of the Beveridge curve, they can as well affect its slope. If the cyclical factor only explains the shifts of the (u,v) curve but is unrelated to the changes of its slope, the hypothesis of a smooth adjustment processes in the labour market to demand shocks will be strongly convulsed. The same holds if dynamic factors necessary for an adjustment process may not be revealed. While applied studies of the Beveridge generally neglect the impacts of cyclical (and structural) factors on its slope, Wall and Zoega (2002) used the unemployment rate and its first-order lag to establish the effect of the business cycle on the intercept.

Table 2 reports a close connection between the changes of the intercepts and the output gap but no relation to the variation of the slopes of the annual Beveridge curves (see columns 2 and 4 of the table). The Durbin-Watson statistic states, however, that both regression models are misspecified. Without looking at additional explanatory variables, positive residual autocorrelation can be eliminated by imposing a Markov process for the errors. When allowing for adjustment by regressing the intercepts of annual (u,v) curves on both current and lagged output gaps, only the former variable turns out to be significant. The insignificance of the lagged output gaps is not altered if the model is extended by an AR(1) error process.

-Table 2 about here-

Both the failure of the cyclical variable to determine the variation of the slope and the irrelevance of its lagged values in explaining changes in the intercept cast strong doubts in the idea of a stable German Beveridge curve in the course of the business cycle. Figure 3 shows the that the ups and downs of the intercepts of the (u,v) curve are qualitatively well in line with the phases of the business cycle. The main difference comes from the fact that the amplitudes of the business cycle turn out to be considerably larger then those of intercept waves.

-Figure 3 about here-

Autocorrelation of the residuals clearly points to an insufficient explanation of the intercepts of the Beveridge curve by only cyclical factors. Although some recent research has doubted the stability of the Beveridge curve (Börsch-Supran, 1991; Wall and Zoega, 2002), most authors have found that the structural factors significantly affected its location. In fact, long term unemployment exerts a significant effect on search effectiveness. The strength of the influence of long term unemployment on the intercept of the (u,v) curve is comparable to that of the output gap (see table 3). Variables describing the institutional framework of the labour market are not significant, possibly due to the relatively short time span of the analysis or multicollinearity problems.

-Table 3 about here-

The negative effect of long-term unemployment on search effectiveness is usually explained by the loss of job skills and motivation with increasing unemployment duration (Budd, Levine and Smith, 1988; Groenewold, 2003). As a result, unemployment hysteresis will arise. Under a hiring rule last-into unemployment first-to be hired the unemployment rate can rise along with the long-term unemployed in which case the causal chain is reversed (Webster, 1999). This simultaneity problem may be treated by instrumenting the long term unemployment regressor by the lagged series. Here, GMM estimation does not show any significance. But, due to the fact that Webster (1999) proves the significance of lagged long-term unemployment for quarterly data, a lag of one year may be a too long time span for an adequate instrument. Hence, the reverse causation hypothesis remains an open question.

A direct test of the relevance of structural and cyclical variables for explaining the intercepts of the (u,v) curve is also carried out by Wall and Zoega (2002) for the UK. In accordance with our results for the German Beveridge curve, only the cyclical variable and long-term unemployment prove to be significant. As long-term unemployment is not instrumented in that study, the authors do not provide any clue on reversed causation. In their analysis, the cyclical variable dominates. Due to a lack of a production index on the regional level, Wall and Zoega used the unemployment rate as a cyclical variable which may overrate the true cyclical effect. Nonetheless, the stability of the British Beveridge curve has been challenged as well.

7 Conclusions

In this paper, the framework of the aggregated Beveridge curve is used to investigate the effectiveness of the job matching process using German regional labour market data. For a fixed matching technology, the Beveridge curve postulates a negative relationship between the unemployment rate and the rate of vacancies, which is efficiently estimated using spatial econometric techniques. The eigenfunction decomposition approach suggested by Griffith (2000, 2003) is the workhorse to identify spatial and non-spatial components. As the significance of the spatial pattern might vary over time, inference is conducted on the base of a spatial SUR model. Econometric estimates of the parameter measuring the shifts of the Beveridge curve over time are obtained. In contrast to findings for the US and the UK, the results provide serious indication that the degree of job mismatch has increased over the last decade. Although the outward shift of the Beveridge curve can be explained by structural factors such as the evolution of long term unemployment, it is also affected by business cycle fluctuations. The role of cyclical factors challenges the stability property of the curve. The relationship might be inappropriate to investigate policy measures directed to improve the mismatch, such as labour market reforms.

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Figure 1: Changes of matching efficiency over time

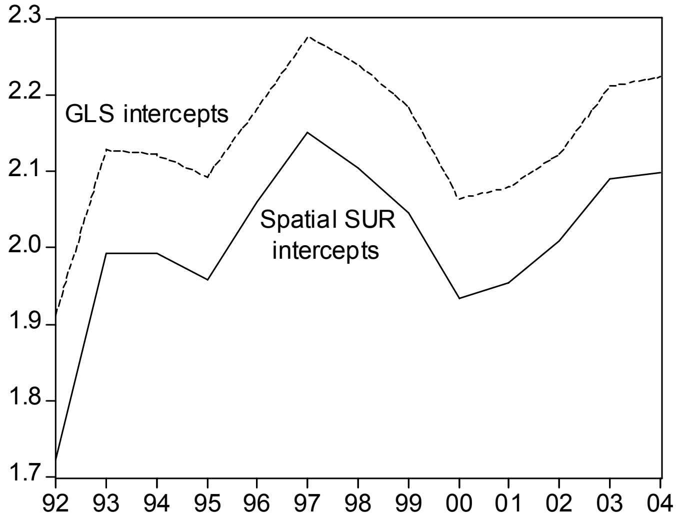

Figure 2: Map patterns of spatial components

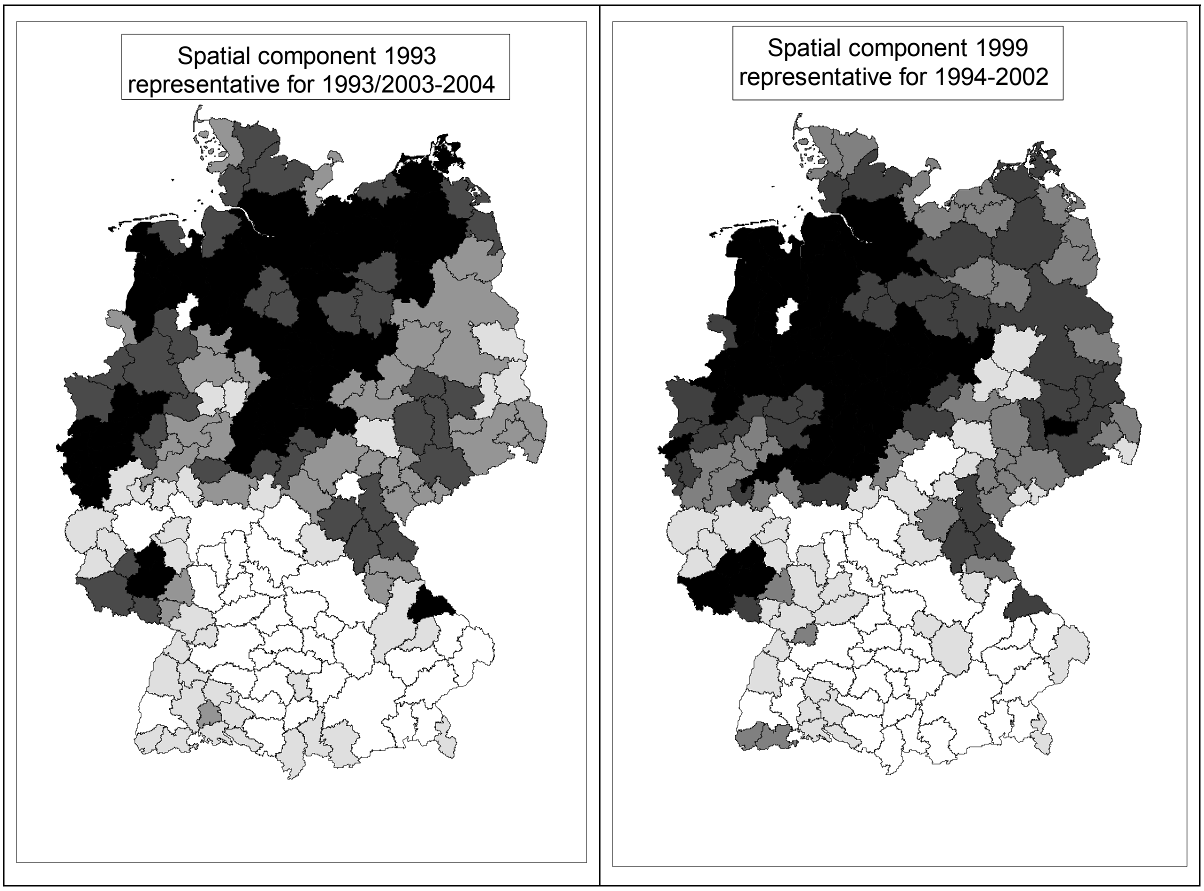

Figure 3: Beveridge curve and business cycle

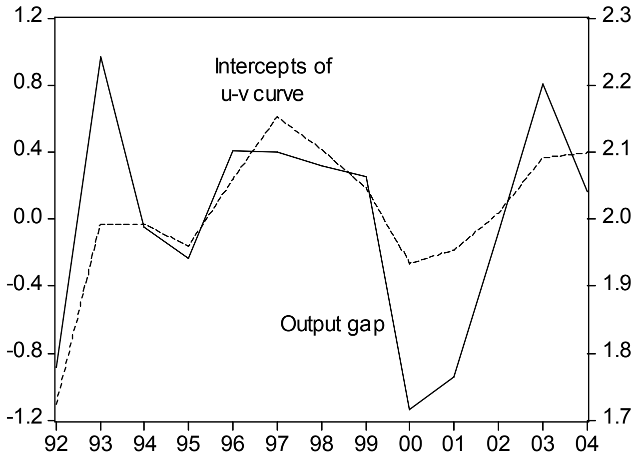

Table 1: Spatial Beveridge curves

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Non-spatial GLS													
Const.	1.912 (0.000)	2.128 (0.000)	2.122 (0.000)	2.093 (0.000)	2.182 (0.000)	2.276 (0.000)	2.240 (0.000)	2.185 (0.000)	2.064 (0.000)	2.079 (0.000)	2.123 (0.000)	2.211 (0.000)	2.224 (0.000)
ln v	-0.095 (0.000)	-0.053 (0.000)	-0.040 (0.000)	-0.036 (0.000)	-0.018 (0.014)	-0.024 (0.000)	-0.028 (0.001)	-0.029 (0.000)	-0.030 (0.000)	-0.018 (0.034)	-0.017 (0.082)	-0.005 (0.309)	-0.022 (0.006)
East	0.360	R^2	0.970	SER	1.006	SSR	2340.0	Wald (I)	935.659	Wald (S)	37.956	PD-W	1.484
MI res	0.755 (0.000)	0.645 (0.000)	0.614 (0.000)	0.594 (0.000)	0.602 (0.000)	0.638 (0.000)	0.688 (0.000)	0.723 (0.000)	0.778 (0.000)	0.870 (0.000)	0.851 (0.000)	0.826 (0.000)	0.806 (0.000)
Spatial SUR													
	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Const.	1.723 (0.000)	1.992 (0.000)	1.992 (0.000)	1.959 (0.000)	2.060 (0.000)	2.152 (0.000)	2.104 (0.000)	2.046 (0.000)	1.934 (0.000)	1.954 (0.000)	2.009 (0.000)	2.091 (0.000)	2.099 (0.000)
ln v	-0.216 (0.000)	-0.116 (0.002)	-0.068 (0.041)	-0.079 (0.042)	-0.030 (0.258)	-0.018 (0.332)	-0.002 (0.479)	0.019 (0.356)	-0.066 (0.100)	-0.160 (0.000)	-0.132 (0.001)	-0.143 (0.000)	-0.127 (0.000)
East	0.784	R^2	0.875	SER	0.180	SSR	69.0	Wald (I)	4259.925	Wald (S)	33.246	P-DW	1.846
MI res	-0.074 (0.829)	-0.093 (0.459)	-0.063 (0.848)	-0.061 (0.907)	-0.084 (0.517)	-0.101 (0.317)	-0.033 (0.744)	0.009 (0.211)	-0.002 (0.231)	-0.051 (0.567)	-0.019 (0.213)	-0.039 (0.263)	-0.025 (0.120)
ev	1,2,3,6,8, 10,13,15, 20,21,33, 39,47	1,2,7,8, 10,13,15, 20,21,24, 33,39,47	1,2,5,7, 10,15,20, 21,24,33 39,47	1,2,5,7, 10,13,15, 20,21,33, 39,47,51	1,2,5,7, 10,15,20, 21,33,47, 50,51,52	1,2,5,7, 10,15,20, 21,33,47, 50,51,52	1,2,5,7, 15,20,21, 33,47,51, 52	1,2,5,7, 15,20,21, 33,47,51, 52	1,2,3,7, 10,15,20, 21,33,47, 50,51,52	1,2,3,6,7, 10,11,13, 15,20,21, 25,27,33, 38,43,52	1,2,3,6,7, 10,15,16, 20,21,25, 27,35,38, 43,47,52	1,2,3,6,7, 10,15,16, 18,20,21, 27,32,33, 35,38,39	1,2,3,6,7 10,11,16, 19,20,21, 27,32,33, 35,38,39, 43,46,47, 52
MC	0.873	0.803	0.785	0.795	0.784	0.777	0.790	0.817	0.871	0.901	0.861	0.814	0.814

Notes:

p-values in brackets below the regression coefficients; R^2: coefficient of determination; SSR: Sum of squared residuals; SER: Standard error of regression; P-DW: Panel Durbin-Watson statistic; MI res: Moran's I values of the residuals; ev: Number of significant eigenvector; MC: Moran's I values of the spatial components; Wald (I) Wald test on equality of intercepts; Wald (S) Wald test on equality of slopes; Critical values for Wald tests: $\chi_{12;0.95} = 23.3$; $\chi_{12;0.99} = 26.2$

Table 2: Location of Beveridge curves and output gap

Dependent variable	Slopes of Beveridge curves		Intercepts of Beveridge curves		Intercepts of Beveridge curves	
Constant	-0.076 (0.002)	-0.059 (0.071)	2.009 (0.000)	2.049 (0.000)	2.028 (0.000)	2.046 (0.000)
Output gap	0.009 (0.787)	0.004 (0.897)	0.114 (0.010)	0.080 (0.002)	0.025 (0.021)	0.087 (0.006)
Output gap (-1)					0.037 (0.140)	0.025 (0.190)
AR(1) error		0.483 (0.105)		0.480 (0.013)		0.472 (0.120)
R^2	0.007	0.325	0.470	0.743	0.554	0.803
SSR	0.053	0.023	0.075	0.014	0.024	0.010
SER	0.070	0.051	0.082	0.039	0.051	0.038
L*	17.299	20.516	15.053	23.632	20.324	22.827
DW	0.676	1.879	0.550	1.793	0.738	1.818

Notes: *p*-values in brackets below the regression coefficients. R^2 coefficient of determination; SSR Sum of squared residuals; SER Standard error of regression; L* log Likelihood; DW Durbin-Watson statistic.

Table 3: Determinants of Beveridge curve shifts

Dependent variable	Intercepts of Beveridge curves					
	OLS	GMM	OLS	OLS	OLS	OLS
Constant	1.306 (0.000)	1.833 (0.000)	1.368 (0.000)	1.983 (0.001)	2.422 (0.008)	2.395 (0.012)
Output gap			0.102 (0.000)	0.103 (0.000)	0.114 (0.001)	0.100 (0.000)
Long-term unemployment	0.015 (0.004)	0.004 (0.358)	0.013 (0.000)	0.012 (0.000)	0.008 (0.092)	0.012 (0.000)
Public employ-ment services				-2.383 (0.122)	-2.784 (0.124)	-2.384 (0.141)
Union density					-1.003 (0.355)	
Taxes to GDP ratio						-0.011 (0.518)
R^2	0.548	0.009	0.921	0.941	0.949	0.945
SSR	0.064	0.048	0.011	0.008	0.006	0.007
SER	0.076	0.064	0.033	0.031	0.032	0.032
L*	16.091		27.430	26.968	25.463	27.352
DW	1.433	1.023	2.331	2.503	2.684	2.445

Notes: *p*-values in brackets below the regression coefficients. R^2 coefficient of determination; SSR Sum of squared residuals; SER Standard error of regression; L* log Likelihood; DW Durbin-Watson statistic.